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Self-adaptive Dynamic Optimization in an Extremum Value Control System

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Abstract: A new method of self-adaptive dynamic optimization for an extremum value control system is presented, the method is successful in solving a difficult problem, which is to keep the continuity and stability of the control system in operation. Once after the parameters of the control plant have drifted, the control system can not work well in the previous method. Therefore, we have to stop to identify the parameters of the control plant and to adjust the parameters of the control system again. The outstanding advantage of the new method is that it can automatically not only identify the parameters of the control plant, but also adapt to the drift of the parameters in the automatic search process for the optimum point. In other words, it is unnecessary for the control system to stop to identify the parameters of the control plant and to adjust that of the control system again. Therefore, it is expected that we could keep a continuous and stable operation of the system by using the new method. It is also expected that this method will play an important role in the desirable industrial process control.
Keywords: self-adaptive dynamic search; optimum point; identification; drift

1. Introduction

There are many extremum value control systems in industrial processes. A combustion control system is a typical example; there exists an extemum value property between working efficiency and the air amount helping combustion. The position of curve which satisfies the extremum value property becomes also different as feeding fuel amount is different. Furthermore there exists a disturbance that can not be measured, for example, the disturbance is caused by changing in heating amount of fuel [1],[2].

There also exists a curve showing the extremum value property between the working efficiency of coal grinder and the amount of feeding coal, where change in the kind and quality of coal is a kind of disturbance which is hardly measured. The grinder used in cement mill is a similar example, too.

The static method of optimum searching can be used in the extremum value control system in order to solve the problem mentioned above by means of the step-by-step direction search for the optimum point. The judgment is based on the sign of the output increment in a step-by-step period by using the static method. The method is correct if the controlled plant is inertialess. If the plant is inertial, the method may also be used when the step-by-step period is long enough. However, if the time constants of dynamic elements are bigger, the static method would result in rather slow search for the optimum point so that it could not be tracked when the property curve is drifted due to disturbances. If the step-by-step period is shortened to increase the speed of search for the optimum point, the search step might disorder the optimum condition so that the control system could not work well, which is especially serious if higher order dynamic elements exist in the controlled plant.

A dynamic step-by-step method for the optimum point search has been presented in reference[1]. Being compared to the static method[2], it is not only fast in the optimum point search to overcome the shortage of the static method, but also suitable for the controlled plant with *N*th order dynamic elements. However, it is not enough convenient for a real extremum value control system: Firstly, it is necessary to know the parameters and structure of the controlled plant, because these parameters have to be measured and be identified if they are not known. Secondly, they are slowly drifted with time in general, these parameters have to be measured and be identified again, and the parameters of control system have to be also adjusted after the control system runs for a longer time. Therefore, it is very necessary to look for a self-adaptive dynamic method for the optimum point search. In the case that the order of the controlled plant is known the new method could automatically not only identify the parameters but also adapt to the drift of the parameters in the process of searching the optimum point. So long as the control system come into use, it could work well all the same. Even after the major overhaul has been done. It is unnecessary to make the parameters of the controlled plant be identified and to make the parameters of control system be adjusted. It is expected that control system will work well as usual.

2. Pre-estimating comparative theory

A step-by-step controller is used in the extremum value control system. Assume the step-by-step period T_0 is changeless, the extremum value controlled plant may be expressed as a cascade form of a non-linear element and a linear element as shown in

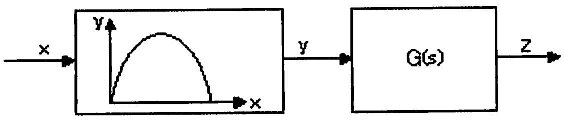


Fig.1 Block diagram of an extremum value control system

The linear part consists of the dynamic elements, of which chracteristic roots are all negative real roots so that its unit step response function $\hbar(t)$ is monotonic to a step change.

In the step-by-step process of searching the optimum point, the output response resulting from the kth step input is as follows:

$$\left.\begin{array}{l} Z(\bar{t}) = 0,\ \bar{t} < k \\ Z(\bar{t}) = \{y(k) - y(k-1)\}h(\bar{t}-k),\ \bar{t} > k \end{array}\right\},$$

where $Z_k(\bar{t})$ and $y(k)$ denote the output change of linear part resulting from the kth input step and the output of non-linear part (input to linear part), respectively. $\bar{t}$ denotes relative time (quantized time), and T_0 expresses step period.

Let input x go a step at every interval of a step-by-step period T_0 from $\bar{t} = 0$, the system output after m steps is expressed as :

$$Z(\bar{t}) = \sum_{k=0}^{m}\{y(k) - y(k-1)\}\hbar(\bar{t}-k),\ \bar{t} > m. \quad (1)$$

The task of extremum value control system with dynamic search scheme for the optimum point in the transient process is to decide the nth step-by-step increment direction of the input after the n-1 th step-by-step step, this can be based on the output change resulting from the input step at step n-1 that is a probing step. The idea of pre-estimating the system output at some time point $\bar{t}$ between the time point of the step n-1 and that of the step n is as follows. It could be done on the basis of the output samples of the system between the time point of the step n-2 and that of the step n-1, if the probing step is not exerted, then the step-by-step increment direction could be judged by comparing the real output and the pre-estimated output.

If the probing step is not be exerted at $\bar{t} = n-1$, the pre-estimated output of the system at $n-1 < \bar{t} < n$ is given as:

$$\hat{Z}(\bar{t}) = \sum_{k=0}^{n-2}\{y(k) - y(k-1)\}\hbar(\bar{t}-k)$$
$$= \sum_{k=0}^{n-2} a_k \hbar(\bar{t}-k) \quad (2)$$

where $a_k = y(k) - y(k-1)$.

If the probing step is exerted at $\bar{t} = n-1$, the real output of the system at $n-1 < \bar{t} < n$ is:

$$Z(\bar{t}) = \sum_{k=0}^{n-1}\{y(k) - y(k-1)\}\hbar(\bar{t}-k)$$
$$= \sum_{k=0}^{n-1} a_k \hbar(\bar{t}-k)$$
$$= \sum_{k=0}^{n-2} a_k \hbar(\bar{t}-k) + a_{n-1}\hbar(\bar{t}-(n-1)). \quad (3)$$

The comparing value is then obtained by subtracting Eq. (2) from Eq. (3) as

$$\tilde{z}(\bar{t}) = z(\bar{t}) - \hat{z}(\bar{t}) = a_{n-1}\hbar(\bar{t}-(n-1))$$
$$= \{y(n-1) - y(n-2)\}\hbar(\bar{t}-(n-1)). \quad (4)$$

$\tilde{Z}(\bar{t})$ is the output response of the control system at $\bar{t}$ resulting from the exerted probing step at $\bar{t} = n-1$. Since $\hbar(\bar{t})$ is monotonic, the sign of $\tilde{Z}(\bar{t})$ is the same with that of $\{y(n\text{-}1)\text{-}y(n\text{-}2)\}$, and the direction of the step-by-step increment may be decided on the sign of $\tilde{Z}(\bar{t})$. This is the basic idea of pre-estimating comparative theory .

The differential value is used to simplify the

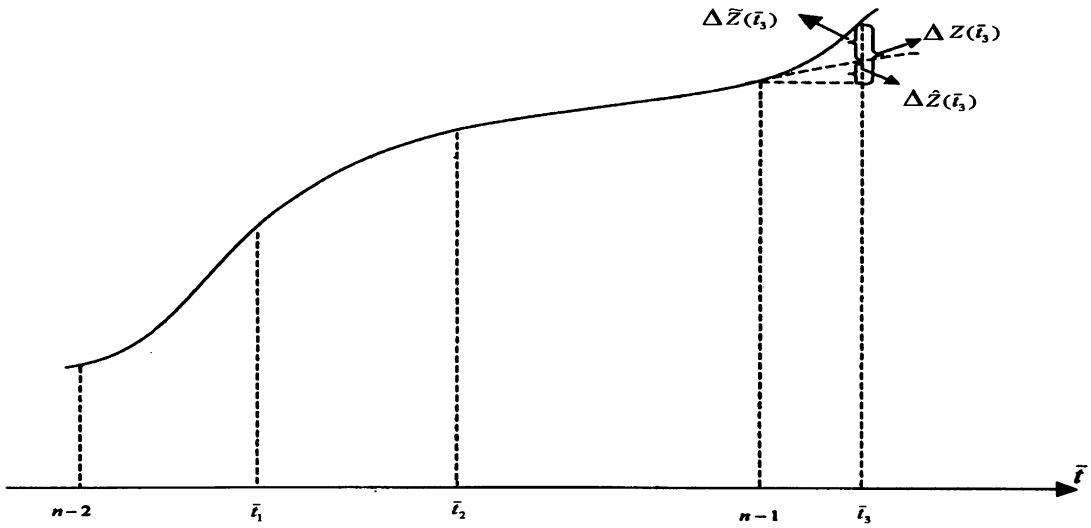


Fig.2 Diagram showing pre-estimating difference comparative theory

computation to decide the direction of step-by-step increment based on the sign of $\Delta\tilde{z}(\bar{t}_3)$ as shown in Fig. 2.

We pointed out in reference [4]:

$$\begin{aligned}\Delta Z(\bar{t}_2) &= Z(\bar{t}_2) - Z(\bar{t}_1)\\ &= \sum_{k=0}^{n-2} a_k\{\hbar(\bar{t}_2 - k) - \hbar(\bar{t}_1 - k)\}\end{aligned} \tag{5}$$

$$\begin{aligned}\Delta\tilde{z}(\bar{t}_3) &= \tilde{z}(\bar{t}_3)\\ &= \{y(n-1) - y(n-2)\}\hbar(\bar{t}_3 - (n-1))\end{aligned} \tag{6}$$

3. Adaptive dynamic algorithm for searching the optimum point

Assuming that the transfer function of linear part in the extremum value control system is given as :

$$G(s) = \frac{1}{(T_1S+1)(T_2S+1)\cdots(T_NS+1)},$$
$$T_1 > T_2 > T_3 \cdots\cdots > T_N > 0. \tag{7}$$

The corresponding unit step response function becomes as follows :

$$\hbar(t) = A_0 + \sum_{i=1}^{N} A_i e^{-\frac{t}{T_i}}, \quad A_0 = G(s)|_{s=0} = 1,$$

and $A_i = (s + \frac{1}{T_i})\frac{1}{s}G(s)|_{s=-\frac{1}{T_i}}$, $i = 1,2,\cdots N$.

If a time is quantized with T_0 we get:

$$\hbar(\bar{t}) = 1 + \sum_{i=1}^{N} A_i e^{-\alpha_i \bar{t}}, \tag{8}$$

$\alpha_i = T_0/T_i$, $\bar{t} = t/T_0$, and T_0 implies step-by-step period.

Assuming each step-by-step period is divided into $2N$ equal intervals, the samples are taken at every dividing point and 2 N+1 samples of the system output would be obtained as shown in Fig.3, the first sampling point after a probing step then becomes the pre-estimating comparative point.

Each difference value could be obtained by subtracting adjoining sample values in turn:

$$\left.\begin{aligned}\Delta Z_l &= Z(n-2+\frac{l}{2N}) - Z(n-2+\frac{l-1}{2N}),\\ \Delta\hat{Z}_{2N+1} &= Z(n-1+\frac{1}{2N}) - Z(n-1), l = 1,2,\cdots 2N\end{aligned}\right\}. \tag{9}$$

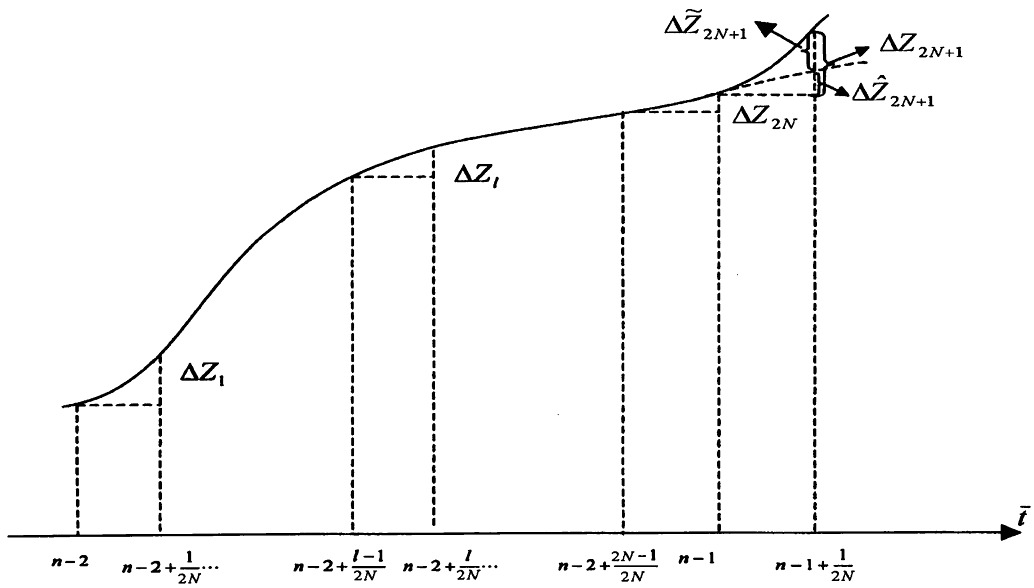
The last equation in Eq.(8) is obtained by using the pre-estimated value, we can derive the following equation from Eqs. (5) and (8) :

$$\{\hbar(\bar{t}_2 - k) - \hbar(\bar{t}_1 - k)\} = \sum_{i=1}^{N} A_i[e^{-\alpha_i(\bar{t}_2 - k)} - e^{-\alpha_i(\bar{t}_1 - k)}]$$

Substitution of this equation into Eq. (5) gives:

$$\begin{aligned}\Delta Z_l &= \sum_{k=0}^{n-2} a_k[\hbar(n-2+\frac{l}{2N}-k) - \hbar(n-2+\frac{l-1}{2N}-k)]\\ &= \sum_{k=0}^{n-2} a_k \sum_{i=1}^{N} A_i[e^{-\alpha_i(n-2+\frac{l}{2N}-K)} - e^{-\alpha_i(n-2+\frac{l-1}{2N}-k)}]\\ &= \sum_{i=1}^{N} e^{-\frac{\alpha_i}{2N}(l-1)}[A_i(e^{-\frac{\alpha_i}{2N}}-1)\sum_{k=0}^{n-2} a_k e^{-\alpha_i(n-2-k)}]\\ &= \sum_{i=1}^{N} \beta_i^{l-1} X_i, \qquad l = 1,2,\cdots,2N+1,\end{aligned} \tag{10}$$

where $\beta_i = e^{-\frac{\alpha_i}{2N}}$, $X_i = A_i(e^{-\frac{\alpha_i}{2N}} - 1)\sum_{k=0}^{n-2} a_k e^{-\alpha_i(n-2-k)}$, $i=1,2,\cdots N$.



ΔZ_{2N+1} : the real difference value of the system output as the probing step is exerted at $\bar{t} = n-1$

$\Delta\hat{Z}_{2N+1}$: pre-estimating difference value of the system output if the probing step is not exerted at $\bar{t} = n-1$

$\Delta\tilde{Z}_{2N+1}$: the deviation in value between the real difference value and the pre-estimating difference value of the system output at sample comparing point .

Fig.3 Diagram showing self-adaptive dynamic optimizing algorithm

The following set of the first $N+1$ simultaneous linear equations may be obtained by letting integer $l=1,2,\cdots, N+1$ respectively in Eq. (10) and expanding the derived equations:

$$\left.\begin{aligned} &X_1 + X_2 + \cdots + X_N = \Delta Z_1 \\ &\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_N X_N = \Delta Z_2 \\ &\qquad\vdots \\ &\beta_1^{N-1} X_1 + \beta_2^{N-1} X_2 + \cdots + \beta_N^{N-1} X_N = \Delta Z_N \\ &\beta_1^N X_1 + \beta_2^N X_2 + \cdots + \beta_N^N X_N = \Delta Z_{N+1} \end{aligned}\right\} \cdot (11)$$

Since these equations are obtained from the relations of the same output response curve So a unique set of roots must exist. The number of equations in Eqs. (11) is N+1. The last equation must then be obtained by the other equation, because the system is of Nth order and there are only N linear independent unknown numbers .

Let the augmented matrix of Eqs. (11) be expressed as :

$$\begin{bmatrix} 1 & 1 & \cdots & 1 & \Delta Z_1 \\ \beta_1 & \beta_2 & \cdots & \beta_N & \Delta Z_2 \\ \beta_1^2 & \beta_2^2 & \cdots & \beta_N^2 & \Delta Z_3 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \beta_1^{N-1} & \beta_2^{N-1} & \cdots & \beta_N^{N-1} & \Delta Z_N \\ \beta_1^N & \beta_2^N & \cdots & \beta_N^N & \Delta Z_{N+1} \end{bmatrix} .$$

Because of the reason stated above , the rank of this augmented matrix must be decreased and only be declined to N. Then its determinant of N+1th order becomes zero:

$$\begin{vmatrix} 1 & 1 & \cdots & 1 & \Delta Z_1 \\ \beta_1 & \beta_2 & \cdots & \beta_N & \Delta Z_2 \\ \beta_1^2 & \beta_2^2 & \cdots & \beta_N^2 & \Delta Z_3 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \beta_1^{N-1} & \beta_2^{N-1} & \cdots & \beta_N^{N-1} & \Delta Z_N \\ \beta_1^N & \beta_2^N & \cdots & \beta_N^N & \Delta Z_{N+1} \end{vmatrix} = 0 . \qquad (12)$$

Expansion of this determinant with respect to the last column yields :

$$\Delta Z_{N+1}D_{N+1} + \Delta Z_N D_N + \cdots + \Delta Z_2 D_2 + \Delta Z_1 D_1 = 0, \tag{13}$$

where: D_{N+1}, $D_N \cdots D_2$, D_1 denote the cofactor of the last column elements such as ΔZ_{N+1}, ΔZ_N, $\cdots \Delta Z_2$, ΔZ_1 in Eq.(12), respectively.

Introducing another integer m, let integer l be m, $m+1$, $m+2$, $\cdots, m+N$ respectively in Eq.(10) and expanding the derived equations, we get:

$$\left.\begin{aligned} &\beta_1^{m-1}X_1 + \cdots + \beta_N^{m-1}X_N = \Delta Z_m \\ &\beta_1^{m}X_1 + \cdots + \beta_N^{m}X_N = \Delta Z_{m+1} \\ &\vdots \\ &\beta_1^{N+m-2}X_1 + \cdots + \beta_N^{N+m-2}X_N = \Delta Z_{N+m-1} \\ &\beta_1^{N+m-1}X_1 + \cdots + \beta_N^{N+m-1}X_N = \Delta Z_{N+m} \end{aligned}\right\}. \tag{14}$$

The corresponding augmented matrix for Eqs. (14) is expressed as follows:

$$\begin{bmatrix} \beta_1^{m-1} & \beta_2^{m-1} & \cdots & \beta_N^{m-1} & \Delta Z_m \\ \beta_1^{m} & \beta_2^{m} & \cdots & \beta_N^{m} & \Delta Z_{m+1} \\ \cdots & \cdots & & \cdots & \cdots \\ \beta_1^{N+m-2} & \beta_2^{N+m-2} & \cdots & \beta_N^{N+m-2} & \Delta Z_{N+m-1} \\ \beta_1^{N+m-1} & \beta_2^{N+m-1} & \cdots & \beta_N^{N+m-1} & \Delta Z_{N+m} \end{bmatrix}.$$

Because of the reason stated previously, the rank of this augmented matrix must be decreased and only be declined to N, then its determinant of $N+1$ order is zero;

$$\begin{vmatrix} \beta_1^{m-1} & \beta_2^{m-1} & \cdots & \beta_N^{m-1} & \Delta Z_m \\ \beta_1^{m} & \beta_2^{m} & \cdots & \beta_N^{m} & \Delta Z_{m+1} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \beta_1^{N+m-2} & \beta_2^{N+m-2} & \cdots & \beta_N^{N+m-2} & \Delta Z_{N+m-1} \\ \beta_1^{N+m-1} & \beta_2^{N+m-1} & \cdots & \beta_N^{N+m-1} & \Delta Z_{N+m} \end{vmatrix} = 0. \tag{15}$$

Obviously,

$$\prod_{i=1}^{N}\beta_i^{m-1}\begin{vmatrix} 1 & 1 & \cdots & 1 & \Delta Z_m \\ \beta_1 & \beta_2 & \cdots & \beta_N & \Delta Z_{m+1} \\ \cdots & \cdots & & \cdots & \cdots \\ \beta_1^{N-1} & \beta_2^{N-1} & \cdots & \beta_N^{N-1} & \Delta Z_{N+m-1} \\ \beta_1^{N} & \beta_2^{N} & \cdots & \beta_N^{N} & \Delta Z_{N+m} \end{vmatrix} = 0. \tag{16}$$

Since $\prod_{i=1}^{N}\beta_i^{m-1} \neq 0$, we then get:

$$\begin{vmatrix} 1 & 1 & \cdots & 1 & \Delta Z_m \\ \beta_1 & \beta_2 & \cdots & \beta_N & \Delta Z_{m+1} \\ \cdots & \cdots & & \cdots & \cdots \\ \beta_1^{N-1} & \beta_2^{N-1} & \cdots & \beta_N^{N-1} & \Delta Z_{N+m-1} \\ \beta_1^{N} & \beta_2^{N} & \cdots & \beta_N^{N} & \Delta Z_{N+m} \end{vmatrix} = 0. \tag{17}$$

Expansion of this determinant with respect to the last column yields:

$$\Delta Z_{m+N}D_{N+1} + \cdots + \Delta Z_{m+1}D_2 + \Delta Z_m D_1 = 0. \tag{18}$$

After letting integer m be 2,3,$\cdots$, N,N+1 respectively in Eq.(18), considering $\Delta \hat{Z}_{2n+1}$ being the pre-estimating difference value of the system output, which synthesizes Eq. (13) and expansion of the derived equations yields the following set of equations:

$$\left.\begin{aligned} &c_1\Delta Z_1 + \cdots + c_N\Delta Z_N = \Delta Z_{N+1} \\ &c_1\Delta Z_2 + \cdots + c_N\Delta Z_{N+1} = \Delta Z_{N+2} \\ &\vdots \\ &c_1\Delta Z_N + \cdots + c_N\Delta Z_{2N-1} = \Delta Z_{2N} \\ &c_1\Delta Z_{N+1} + \cdots + c_N\Delta Z_{2N} = \Delta \hat{Z}_{2N+1} \end{aligned}\right\}, \tag{19}$$

where $c_i = -D_i/D_{N+1}$, i=1, 2, 3$\cdots N$.

The augmented matrix of Eqs. (19) becomes as follows :

$$\begin{bmatrix} \Delta Z_1 & \Delta Z_2 & \cdots & \Delta Z_N & \Delta Z_{N+1} \\ \Delta Z_2 & \Delta Z_3 & \cdots & \Delta Z_{N+1} & \Delta Z_{N+2} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \Delta Z_N & \Delta Z_{N+1} & \cdots & \Delta Z_{2N-1} & \Delta Z_{2N} \\ \Delta Z_{N+1} & \Delta Z_{N+2} & \cdots & \Delta Z_{2N} & \Delta \hat{Z}_{2N+1} \end{bmatrix}.$$

The rank of the augmented matrix with $N+1$ order must decrease to N, because there are only N independent unknown variables c_1, c_2, $\cdots$,c_N. We then get the relation:

$$\begin{vmatrix} \Delta Z_1 & \Delta Z_2 & \cdots & \Delta Z_N & \Delta Z_{N+1} \\ \Delta Z_2 & \Delta Z_3 & \cdots & \Delta Z_{N+1} & \Delta Z_{N+2} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \Delta Z_N & \Delta Z_{N+1} & \cdots & \Delta Z_{2N-1} & \Delta Z_{2N} \\ \Delta Z_{N+1} & \Delta Z_{N+2} & \cdots & \Delta Z_{2N} & \Delta \hat{Z}_{2N+1} \end{vmatrix} = 0. \tag{20}$$

From the definition of the comparative value, $\Delta\tilde{Z}_{2N+1} = \Delta Z_{2N+1} - \Delta\hat{Z}_{2N+1}$, we then get

$$\Delta Z_{2N+1} = \Delta\hat{Z}_{2N+1} + \Delta\tilde{Z}_{2N+1} \quad . \tag{21}$$

According to Eq. (21), Eq. (20) then becomes:

$$\begin{vmatrix} \Delta Z_1 & \Delta Z_2 & \cdots & \Delta Z_N & \Delta Z_{N+1} \\ \Delta Z_2 & \Delta Z_3 & \cdots & \Delta Z_{N+1} & \Delta Z_{N+2} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \Delta Z_N & \Delta Z_{N+1} & \cdots & \Delta Z_{2N-1} & \Delta Z_{2N} \\ \Delta Z_{N+1} & \Delta Z_{N+2} & \cdots & \Delta Z_{2N} & \Delta Z_{2N+1} \end{vmatrix}$$

$$= \begin{vmatrix} \Delta Z_1 & \cdots & \Delta Z_N & \Delta Z_{N+1} \\ \Delta Z_2 & \cdots & \Delta Z_{N+1} & \Delta Z_{N+2} \\ \cdots & \cdots & \cdots & \cdots \\ \Delta Z_N & \cdots & \Delta Z_{2N-1} & \Delta Z_{2N} \\ \Delta Z_{N+1} & \cdots & \Delta Z_{2N} & \Delta\hat{Z}_{2N+1} + \Delta\tilde{Z}_{2N+1} \end{vmatrix}$$

$$= \begin{vmatrix} \Delta Z_1 & \cdots & \Delta Z_N & \Delta Z_{N+1} \\ \Delta Z_2 & \cdots & \Delta Z_{N+1} & \Delta Z_{N+2} \\ \cdots & \cdots & \cdots & \cdots \\ \Delta Z_N & \cdots & \Delta Z_{2N-1} & \Delta Z_{2N} \\ \Delta Z_{N+1} & \cdots & \Delta Z_{2N} & \Delta\hat{Z}_{2N+1} \end{vmatrix}$$

$$+ \begin{vmatrix} \Delta Z_1 & \cdots & \Delta Z_N & 0 \\ \Delta Z_2 & \cdots & \Delta Z_{N+1} & 0 \\ \cdots & \cdots & \cdots & \cdots \\ \Delta Z_N & \cdots & \Delta Z_{2N-1} & 0 \\ \Delta Z_{N+1} & \cdots & \Delta Z_{2N} & \Delta\tilde{Z}_{2N+1} \end{vmatrix}$$

$$= 0 + \Delta\tilde{Z}_{2N+1} \begin{vmatrix} \Delta Z_1 & \Delta Z_2 & \cdots & \Delta Z_N \\ \Delta Z_2 & \Delta Z_3 & \cdots & \Delta Z_{N+1} \\ \cdots & \cdots & \cdots & \cdots \\ \Delta Z_{N-1} & \Delta Z_N & \cdots & \Delta Z_{2N-2} \\ \Delta Z_N & \Delta Z_{N+1} & \cdots & \Delta Z_{2N-1} \end{vmatrix} .$$

As a result, the expression of comparative value is obtained as

$$\Delta\tilde{Z}_{2N+1} = \frac{\begin{vmatrix} \Delta Z_1 & \Delta Z_2 & \cdots & \Delta Z_{N+1} \\ \Delta Z_2 & \Delta Z_3 & \cdots & \Delta Z_{N+2} \\ \cdots & \cdots & \cdots & \cdots \\ \Delta Z_{N+1} & \Delta Z_{N+2} & \cdots & \Delta Z_{2N+1} \end{vmatrix}}{\begin{vmatrix} \Delta Z_1 & \Delta Z_2 & \cdots & \Delta Z_N \\ \Delta Z_2 & \Delta Z_3 & \cdots & \Delta Z_{N+1} \\ \cdots & \cdots & \cdots & \cdots \\ \Delta Z_N & \Delta Z_{N+1} & \cdots & \Delta Z_{2N-1} \end{vmatrix}} \cdot \tag{22}$$

Therefore it becomes clear that the direction of the step-by-step increment can be decided by using Eq.(22) with the output sample values, $\Delta Z_1, \Delta Z_2, \cdots, \Delta Z_{2N+1}$, of the extremum value control system. Consequently, the expression of judging the step-by-step direction becomes as follows:

$$\mathrm{sgn}[\Delta x_n] = \mathrm{sgn}[\Delta\tilde{Z}_{2N+1}\Delta x(n-1)] \quad , \tag{23}$$

where $\mathrm{sgn}[x]$ implies the sign of x.

4. Conclusion

It turns out from Eqs. (22) and (23) that the expression of judging the step-by-step direction is independent of the time constants T_1, $T_2 \cdots\cdots T_N$ of the dynamic elements. Therefore slow variation of these parameters with time can not affect the correctness of judging expression at all. In other words , Eq. (23) can adapt automatically to the variation of the parameters in the controlled plant. Consequently, this method can be known as self-adaptive dynamic optimizing method [5],[6].The extremum value control system designed with this method can automatically not only identify the parameters of the controlled plant , but also adapt to the their variation. Therefore, it is dispensable to identify the parameters of the controlled plant and to adjust the parameters of control system again for overhaul or the other factors resulting from the drift of parameters. Accordingly, it will play an important role in control of the desirable real industrial processes.

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